

AN EFFICIENT REAL-TIME DATA COLLECTION MODEL FOR  
MULTIVARIATE SENSORS IN INTERNET OF THINGS (IOT) APPLICATIONS

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A thesis submitted in  
fulfillment of requirement for the award of  
Doctor of Philosophy in Electrical Engineering

Faculty of Electrical and Electronic Engineering  
Universiti Tun Hussein Onn Malaysia

MAY 2019

For my beloved mother, father, wife, sons, brothers, sisters, family



## ACKNOWLEDGEMENT

First of all, praise and thanksgiving to Allah for the blessing of mind and health and “Tofiqime” to complete this thesis. In spite of the fact that my name is printed on the cover of this thesis, the word “I” does not appear within its chapters. I do this to pay tribute to the myriad contributions of my supervisors and mentors, and the support of my family and friends. To my supervisors Assoc. Prof. Dr. Jiwa bin Abdullah and Dr. Ansar Jamil, thank you for your constant guidance and endless patience towards the completion of this thesis. Without your insights and encouragement, this thesis would not have been completed. To my parents Abdullwahab and Fauzia: I owe you for your love, affection and sacrifice. Thank you for giving me the freedom and opportunity to pursue my studies, and forgive me for not being there, when you needed me the most. To my wife Salaw, thank you for believing in me, and for your patience during so many late nights, many of them unanticipated. To my sons Nawaf and Muntaser: Every morning when you wake me up, I feel joy and inspiration. Thank you for things which you do not even know you have done for me -I can even write another thesis. To my brothers and sisters: You are always happy with my every success, thanks a lot for your moral supports. To my friend Adel Yahya Ashype thanks for everything. To UTHM University and the staffs of Faculty of Electrical and Electronic Engineering: Thanks for providing me with an excellent research environment and the necessary resources to undertake this research. To Yemen government and Hodeidah University: Thank you for support me. Last but not least, I would like to thank a person who contributes to complete my final thesis report directly or indirectly. I would like to acknowledge him/her helps, which was necessary to complete this.

## ABSTRACT

In the applications of the Internet of Things (IoT), sensor board depends on a battery that has a limited lifetime to function. Furthermore, the IoT sensor board with multivariate sensors influences the battery lifetime since there is additional data transmissions that must be supported by the board causing it to drain the battery much faster than the sensor board with one sensor. The main aim of this thesis is to increase the battery life of the IoT sensor node. To do so, a number of proposals are presented. First, an updating data strategy denoted as an efficient data collection and dissemination (EDCD) is proposed. EDCD aims to save the energy consumption of the IoT sensor board with multiple sensors by means of reducing the number of transmission packets, if no significant change is reported by the payload sensing block; second is proposed a validity of the measuring sensor reading at node level (VSNL) algorithm. VSNL aims to avoid transmitting any incorrect data, which will help in saving the energy consumption; third, an adaptive threshold and new metric for multivariate data reduction models such as principal component analysis – based (PCA-B) and multiple linear regression – based (MLR-B) have been proposed. In addition, proposed a payload data reduction algorithm (APRS). APRS aims to reduce the transmitted packet size for each sensed payload, which that will help in saving the energy of the IoT sensor board. This work provides an extensive analysis for the design and performance evaluation of real-time data collection model for multivariate sensors in IoT applications. Finally, an efficient real-time data collection model for multivariate sensors in IoT applications (RDCM). RDCM integrated EDCD, VSNL, PCA-B/MLR-B and APRS and the ability to prolong sensor board battery lifetime, which that satisfied by reducing number of transmissions and payload packet size, and also increase the accuracy of data validation. Performance of the proposed algorithms was evaluated through simulation by utilising various real-time datasets. The average of the total percentage of energy saved by applied RDCM to real-time data sets injected with various percentage of errors for all nodes is 98%.

## ABSTRAK

Dalam aplikasi Internet of Things (IoT), papan sensor bergantung kepada bateri yang mempunyai jangka hayat yang terhad untuk berfungsi. Selain itu, papan sensor IoT dengan sensor pelbagai variat mempengaruhi jangka hayat bateri memandangkan terdapatnya penghantaran data tambahan yang perlu disokong oleh papan tersebut sehingga ia menyebabkan pengurangan bateri berlaku dengan lebih cepat daripada papan sensor dengan satu sensor sahaja. Untuk mencapai matlamat utama tesis ini; pertama, strategi pengemaskinian data yang dikenali sebagai Algoritma Kutipan Data dan Agihan (EDCD) telah dicadangkan. EDCD bertujuan untuk menjimatkan penggunaan tenaga oleh papan sensor IoT dengan pelbagai sensor dengan cara mengurangkan bilangan penghantaran paket, jika tiada perubahan penting dilaporkan oleh blok sensor muatan; kedua, semak kesahihan membaca bacaan pengukur di peringkat nod (VSNL) telah dicadangkan. VSNL mensasarkan untuk mengelakkan penghantaran data yang salah, yang akan membantu dalam penjimatan penggunaan tenaga serta meningkatkan ketepatan sistem; ketiga, satu nilai ambang mudah suai dan matrik baharu bagi model pengurangan data pelbagai sumber yang berasaskan kepada penganalisis koponen utama (PCA) dan yang berasaskan kepada linear regressi berbilang adalah di cadangkan. Seterusnya juga dicadangkan satu algoritma pengurangan data muatan di kenali sebagai APRS. APRS bertujuan untuk mengurangkan saiz paket yang akan dihantar bagi setiap muatan data sensor yang boleh menjimatkan tenaga papan sensor IoT. Kerja ini menyediakan satu analisis yang terperinci untuk reka bentuk dan penilaian prestasi model pengumpulan pelbagai variasi data masa nyata dengan pelbagai variasi sensor untuk aplikasi IoT. Akhirnya, mencadangkan Model Pengumpulan Data Nyata untuk papan sensor IoT dengan pelbagai variasi sensor yang dipanggil RDCM. RDCM bertujuan untuk memanjangkan jangka hayat bateri bagi papan sensor, yang selari dengan pengurangan bilangan penghantaran dan saiz paket muatan, dan juga meningkatkan pengesahan data

yang tepat. Sumbangan RDCM berdasarkan skim-skim tersebut (EDCD, VSNL, PCA-B / MLR-B dan APRS). Prestasi algoritma yang dicadangkan dinilai melalui simulasi dengan menggunakan pelbagai dataset masa nyata. Purata peratusan penjimatan tenaga oleh RDCM yang diaplikasikan untuk set data masa nyata yang disuntik dengan pelbagai peratusan kesilapan untuk semua nod adalah 98%.



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## LIST OF SYMBOLS

$D[t]$	-	the representation variable real-time sensed (reduced sensed data)
$D_S$	-	Node Data size ( $D_S$ ) is all the measured values read by the all sensors $S_i$ , $i=1,2,...,n$
$E$	-	the total energy consumption during a specific period.
$ES$	-	Abbreviation to Exactly same (ES), the value of absolute change between ( $S_{V(t-1)}$ ) and ( $S_{V(t)}$ ) is "zero".
$E_R, E_T$	-	the energy consumption for transmission of data in the reduction phase and retraining phase, respectively.
$E_{RM}$	-	the energy consumption per sample in the Reduction mode (RM)
$E_{Byte}, E_{bit}$	-	the energy consumption per Byte and bits, respectively.
$E_{N-RM}$	-	the energy consumption per sample in the Non-Reduction Mode (N-RM)
$E_{total}$	-	the total energy consumption during a specific period.
$F_S$	-	the binary parameter to send data / not send data
$R_f$	-	The relative difference
$K$	-	the total number of transmissions samples
$K_1, K_2, K_3$	-	the number of transmit samples during data collection in N-RM, RM, and RTM, respectively.
$L$	-	the total number of bits required to represent relative difference $\pm RD_i$
$L1$	-	the total number of bits for $D[t]$ at the fusion center
$m$	-	the required bits to represent $ RD_i $
$n$	-	the number of sensors on the same IoT sensor board
$n_R, n_T$	-	the number of message transmissions in the reduction phase, the number of UFM
$Nd$	-	Number of nodes

$P_{Lenght}$	-	the length (bits) of payload per sample
$PC$	-	the number of Principal Components (PC) for PCA
$r\%$	-	the data reduction ratio
$RT_n\%$	-	the average percentage of power saved in transmission phase
$RD_{1 \times n}$	-	the model data reduction ratio
$S(t)$	-	the current measured value by the sensor
$S(t - 1)$	-	the last measured value transmitted by the sensor.
$S_i$	-	Array of sensors and $i$ -th Refer to the index of sensor
$S_{S_i}$	-	State of the sensor ( $S_{S_i} \in [1,0]$ ) is a one-bit value to describe the correlation between the current measuring ( $S_t$ ) and the previous transmitted measuring value( $S_{t-1}$ ).
$S_s$	-	A row data for sensors state value
$S_d, S_R$	-	the size of the original sensed data and of model reference parameters
$S_{1 \times n} [t]$	-	the new Real-time sensed data vector at the time t
$S_{1 \times n} [t - 1]$	-	the last sensed data transmitted vector to the fusion center at t-1
$Sb_{1 \times n}$	-	the signs vector in order to manage the negative and none-negative RD
$\hat{S}_{1 \times n} [t]$	-	the predictions sensed data at Sensor board / Fusion
$t$	-	refer to the current time
$t - 1$	-	refer to the last time transmitted to the sink
$\beta$	-	the allowed amount of difference (select by the Sink)

## LIST OF ABBREVIATIONS

ABSD	- An Adaptive Buffer Sensed Data
ADAT	- A technique to Reduce Aggregated Data
AM	- Arithmetic Mean
ANN	- Artificial Neural Networks
APCADR	- Adaptive PCADR
APRS	- Adaptive Real-Time Payload Data Reduction Scheme
AR	- Autoregressive
ARIMA	- Autoregressive Integrated Moving Average
AT	- Ambient Temperature
CCIPCA	- Candid Covariance-Free Incremental PCA
CH	- Cluster Head
CMF	- Confidence Measure Factor
CoPeST	- Collective forecast exploiting temporal-spatial correlation
CSE	- Constant Error
<i>cor</i>	- Correlation
DVA	- Data validation algorithm
ED	- Euclidean distance
EDCD	- An Efficient Data Collection For IoT /WSN Applications
ED-HD	- Error Detection based Historic Data
ED-NN	- Error Detection based Nearest Neighbors
ED-RT	- Error Detection in Real-Time
ES	- Exponential Smoothing
EV	- Event
<i>FD</i>	- False Detection
GM	- Geometric mean
GUI	- Graphic user interface
HLMS	- Hierarchical Least-Mean-Square
HM	- Harmonic mean
IBRL	- Intel Research Lab dataset
IoT	- Internet of Things

KPCA	- kernel principal component analysis
LMS	- Least Mean Square
LUCE	- Lausanne Urban Canopy Experiment
LZW	- Lempel–Ziv–Welch
MA	- Moving Average
MCU	- microcontroller
MD	- Median
MLP	- multi-layer perceptron
MLR /	- Multiple / simple linear Regression
LR	
MLR-B	- Multiple linear Regression –based Model
MSD	- mean-square derivation
NC	- Normal change
OCPCC	- One Class Principal Component Classifier
OCSVM	- one class quarter sphere support vector machine
OTE	- Outlier Error
PCA	- Principal Component Analysis
PCA-B	- Principal Component Analysis – based Model
PCADR	- PCA Data Reduction
RD	- Relative Difference
RDCM	- An Efficient Real-Time Data Collection Model For Multivariate Sensors in IoT Applications
RE	- Range Error
RH	- Relative Humidity
RMSE	- Root Mean Square Error
RTD	- real-time data
SD	- Standard deviation
SMG	- Sensor Measure's Gradient
ST	- Surface Temperature
TSF	- Time Series Forecasting
UFM	- Updating Frequency Metric
VSNL	- Validity of the measuring sensor reading at node level
WSN	- Wireless sensor networks

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PTTA UTHM  
PERPUSTAKAAN TUNKU TUN AMINAH



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